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Multi-asset Scenario Building for Trend-Following Trading Strategies

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Abstract

This paper presents a new method for improving the performance of trend-following trading strategies. This new approach improves the inherent problem of trend-following strategies, which is their lagging signals. We simulate alternative price paths of financial assets using a modification of a distribution-free, semi-parametric approach that combines a GARCH-type process with historical simulation. These simulated price paths are used to construct and optimize trend-following trading strategies. The study is conducted in a multi-asset environment. Our empirical results demonstrate the superior performance for multiple assets on a large set of performance metrics compared to widely applied trend-following trading strategies. The results are robust to variations in input specifications, such as tested time and lookback period, number of simulated price paths, and price steps per simulation, but also in terms of trading strategy calibration and market positioning (long-only, long–short, short-only).

Keywords: scenario building trend-following momentum trading strategy moving average filtered historical simulation

JEL Classification: G11, G15, G19, G23

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1 Introduction

Decision support systems have grown in popularity in almost all fields of economics, particularly in finance. Board, Sutcliffe, and Ziemba (1999) and Zopounidis, Doumpos, and Niklis (2018) discuss the properties of financial problems and explain why they lend themselves so readily to applications of decision support systems. Typically, they summarize, the objective is to maximize the return or to minimize the risk, while the variables are mostly quantitative in nature and are often expressed in monetary terms. This allows a firm representation of the complex reality by means of a model. The adoption of operational research methods by financial practitioners is additionally driven by their familiarity with quantitative analysis. This, together with the increased availability of data and the enhanced processing power of computers, has led to applications of decision support systems from operations research in the area of portfolio selection (see for example Markowitz (1952) or Fabozzi, Huang, and Zhou (2010)) and the pricing of financial instruments (see for example Boyle (1977)). In particular, the pricing of derivative securities heavily relies on simulation methods (see Broadie and Glasserman (1997) and Grant, Vora, and Weeks (1997)). As the price evolution of a financial asset is just one realization of a stochastic process that is one out of many possible histories, it is interesting to build alternative price paths of financial assets in order to build more robust trading strategies. In particular—and in contrast to the abovementioned literature—this paper uses a distribution-agnostic simulation process to build scenarios that does not require a prior definition of the probability distribution of the return process. The scenario building process empirically explored in this paper is based on Barone-Adesi, Giannopoulos, and Vosper (1999), a process that they call filtered historical simulation. It combines the empirical distribution of past returns and nonlinear econometric models to simulate possible future values of an asset in the days ahead. From a statistical perspective it is a semi-parametric model and provides a range of advantages over other simulation approaches. Firstly, using the empirical distribution of past returns implies that the price series is not assumed to follow any kind of theoretical probability distribution. Other well-known simulation models, such as the Monte Carlo method in Broadie and Glasserman (1997), draw innovations from predetermined theoretical distributions, thereby smoothing the empirical distribution of the data and consequently introducing errors that might lead to the underestimation of the probability of certain scenarios due to a lack of implied skewness and kurtosis in the assumed distribution. Secondly, from a computational perspective, the parallel bootstrapping process implicitly handles the cross dependencies among the data series. Our simulation process is therefore able to reduce the dimensions of the problem dramatically as the number of parameters and the time needed to carry out the computation increase only linearly with the number of assets that are handled. This is in contrast to models that rely on estimates of the variance–covariance matrix to capture the cross dependencies, where the dimension of the problem is a quadratic function of the number of assets. The artificial price paths generated by the scenario building process are used to improve trend-following trading strategies based on moving average cross systems, known from the field of technical analysis (e.g., Murphy (1999)). Moving average cross systems are widely applied in the financial industry (see for example Man Group's working paper by Granger, Greenig, Harvey, Rattray, and Zou (2014) or AQR Capital Management's work by Hurst, Ooi, and Pedersen (2017)) and are found to be a good instrument for market timing (see Marshall, Nguyen, and Visaltanachoti (2014)). However, a trend-following strategy is typically lagging in nature, "as it never anticipates; it only reacts" (see Murphy (1999)). While this rule-based investment decision support system has proved capable of helping investors not fall victim to behavioral biases, typically the change in signal is delayed thereby missing the optimal timing for opening and closing the respective trades. While most of the existing literature focuses on finding either the best-performing moving average calibration or the best trend-filtering device, our paper adds to the literature by combining trend-following trading strategies as a financial decision support system with a simulation approach to optimize the timing of the trading signal generation by extracting structural information from observed price data, irrespective of the calibration of the trading strategy itself.

This paper is organized as follows: We start our paper with a literature review to point out the most important empirical findings on trend-following trading strategies and a discussion of the history and evolution of asset price simulation in Section 2. We continue with a theoretical part, in Section 3, where we explain the scenario building process applied in this paper. We provide an overview of our model parametrization for our baseline results in Section 3.1. The subsequent section, 3.2, provides an insight into our simulated price series. Section 4 focuses on the tested trading strategies. Subsection 4.1 explains the trend-following benchmark strategy that we are trying to outperform in this paper. The following section, 4.2, covers our first optimized trading strategy, named the "median simulated price strategy", and explains its construction. Then, we review the construction of the "probability strategy"—our second optimized trading strategy—in Section 4.3. Section 5 contains all the empirical results of our study. In Sections 5.1 and 5.2 we comment our main empirical results. We challenge our empirical findings in various robustness checks, which are available in our "Appendix to Multi-asset Scenario Building for Trend-Following Trading Strategies".[1] Section 6 concludes this paper with a final review of our main findings and a short summary.

[1] Online appendix.

2 Literature Review

Trend-following trading strategies are widely researched in both academia and the financial industry. While financial professionals were early adopters of trend-following mechanisms carried over from technical analysis, academia has generally shown skepticism with regard to their use for building investment decisions (see among others Fama and Blume (1966), Jensen and Benington (1970), Pinches (1970), and Treynor and Ferguson (1985)). Contradicting the widespread understanding that technical analysis—the use of historical price and volume information to predict future asset price movements—clashes with the efficient market hypothesis, Bessembinder and Kalok (1998) argue that efficient markets and technical analysis can coexist; that is to say, that the forecasting power of technical analysis does not need to be inconsistent with market efficiency. Kandel and Stambaugh (1996) argue that weak evidence of stock return predictability in terms of classical statistical methods can still be economically significant, such that an investor changes his or her allocation accordingly. Very early studies, such as those of Horne and Parker (1967), James (1968), and Goldberg and Schulmeister (1988), address the performance of moving average crosses and present contradicting results. Brock, Lakonishok, and LeBaron (1992) conduct an in-depth study on the performance of simple technical trading rules and simultaneously determine the best-performing calibration of the respective technical indicator. They assign a simple set of technical trading rules significant forecasting power regarding changes in the Dow Jones Industrial Average. Some years later, Sullivan, Timmermann, and White (1999) reexamined the study by Brock et al. (1992) in a more rigorous setup to also account for possible data-snooping traps. Again—and while not only testing moving average cross strategies—each study reports a different calibration under which the moving average strategy performs best. On top of this, Sullivan et al. (1999) document that what is the best-performing moving average cross calibration varies over time. All these contradictory findings regarding the calibration and calculation of trend-filtering devices clearly show the effort that academia and the financial industry have put into this field of research and, therefore, indicate its importance. A recent study by Hurst et al. (2017) documents the strong performance of trend-following trading strategies over a sample of 137 years of data, however, and in contrast to the above cited works, they do not optimize their trend-following model but apply well-known standard calibrations on which to base their empirical analysis. As we are not interested in fitting our trend-following model to the data but rather want to improve the overall signal generation process for entering and exiting a trade, we follow the approach of Hurst et al. (2017) and apply widely used standard calibrations for the moving average cross strategy. To do so, we apply a scenario building process that evolved from historical simulation and use a bootstrapping algorithm. Scenario building models are relied on heavily in financial risk management, where, for example, RiskMetrics—a model based on the variance–covariance of historical realized returns—has been used for years (see Zangari (1996) or Mina and Xiao (2001)) and is still taught in academia. The original model assumes that the data follows a theoretical, often a Gaussian, distribution with constant mean and variance. This linear Value-at-Risk model therefore imposes strong assumptions about the underlying data, which are confuted or at least challenged by the empirical findings of financial research (see for example Kendall (1953) or Mandelbrot (1963)). One can also observe that asset prices can move much more strongly in each direction than a Gaussian distribution predicts. As a possible solution, Embrechts, Klüppelberg, and Mikosch (1997) and Longin (2000) propose using the extreme value theory, which helps overcome the problem of underestimating outliers in the distribution but has other shortcomings. Academics and practitioners moved to simulations to assess the risk of a portfolio or price financial instruments (see for example Broadie and Glasserman (1997) or Grant et al. (1997)) to avoid the limitations of linear models. One of the most famous methods is the Monte Carlo simulation, which is based on random numbers drawn from a theoretical distribution function. As with the linear model, the Monte Carlo method usually relies on a Gaussian distribution. This yields to the same problems as above: using a distribution function that does not fit the empirical distribution of most assets and therefore also limiting the movement of asset prices in each direction. Gains and losses are therefore limited to around three to four standard deviations using a large enough set of simulations. Additionally, in a multi-asset context the Monte Carlo method is based on historical correlations between the assets. In times of market stress however, the correlations between assets typically move toward one, which leads the Monte Carlo method to possibly underestimate losses. To circumvent this problem, the variance–covariance matrix can be estimated more frequently, which increases the computational effort needed in an already computationally intense algorithm. Having identified the problem that asset returns cannot be properly described using a theoretical distribution, the industry has moved to historical simulation, which is based on observed historical price changes. The rationale behind using historical returns instead of using a theoretical distribution is that we also want to consider extreme events, which are not properly captured in most theoretical distributions. This, however, requires using long time series data to ensure our data sample contains these extreme events we want to include in our simulation. Additionally, and this leads to more severe problems, the approach does not take into account the fact that asset risks can evolve over time. Together with the implied assumptions of independent and identically distributed returns the risk might be underestimated (see for example Vlaar and Palm (1993) or Vlaar (2000)). Barone-Adesi, Giannopoulos, and Bourgoin (1998) and Barone-Adesi et al. (1999)

tackle these problems and present a model called "filtered historical simulation". They suggest randomly picking standardized returns from historical returns. Afterward, standardized returns need to be scaled by the current volatility the asset experiences if they are to be used as innovations in a conditional variance equation for the scenario building process that models both the future price of an asset and its variance. This approach allows the simulation of the entire distribution of asset returns. Filtered historical simulation is the basis of our scenario building process and we discuss it in more detail in the next section.

3 Scenario Building Process

Filtered historical simulation has been developed to avoid the drawbacks mentioned above. Particularly, filtered historical simulation does not rely on a specific return distribution and it does take into account the existence of volatility clustering, fat tails, and the leverage effect (see Mandelbrot (1963) and Black (1976)). Unlike in historical simulation, returns are first scaled by the volatility that prevails on that specific day and then are multiplied by the current volatility forecast. This scaling process is necessary to make the past returns stationary and to adjust them such that they are suitable innovations for the simulation process. The rescaling allows the historical returns to reflect the current volatility conditions prevailing in the markets. Below, we follow Barone-Adesi et al. (1999) to demonstrate how our scenarios are constructed.

The two most important variables we have to specify in the scenario building process are the number of simulation runs we want to perform (the number of artificial price paths we want to simulate) and how many days ahead we want to simulate prices into the future. In our baseline model we choose the number of simulations to be 200 and we simulate each price path 10 days ahead. We will address the days-ahead issue in more detail in the robustness checks in the additional appendix to this paper and provide insights into how to specify this parameter. We fit a GARCH model based on an initial data sample, which in our case is specified to be at least 100 daily observations. Estimating the GARCH model forms residual returns from the raw return data. To be applicable in our simulation process, these residual returns are filtered in order to become independent and identically distributed. Our algorithm therefore also removes serial correlation and volatility clusters if the data contains such structures. Barone-Adesi et al. (1999) call their approach semi-parametric since it combines non-parametric historical simulation with the parametric GARCH model.
The standard model used in Barone-Adesi et al. (1999) and demonstrated here as our baseline model is the GARCH(1,1) model with a moving average term (θ) and

an autoregressive term (μ). Using this notation, our estimates of the residuals are ϵ_t and the variance is h_t.
The conditional mean equation can be written as follows:

$$r_t = \mu r_{t-1} + \theta\epsilon_{t-1} + \epsilon_t \qquad \epsilon \sim \mathcal{N}(0, h_t). \tag{1}$$

The conditional variance equation can be written as follows:

$$h_t = \omega + \alpha(\epsilon_{t-1} - \gamma)^2 + \beta h_{t-1}. \tag{2}$$

The GARCH equation (2) defines the variation of ϵ_t as a function of a constant, ω, plus two terms reflecting the contributions of the most recent surprise, ϵ_{t-1}, and the last period's volatility, h_{t-1}, respectively. The constant α determines the influence of the most recent observation whereas γ determines its asymmetry. We divide the estimated residuals, $\hat{\epsilon_t}$, by the corresponding volatility estimate, $\sqrt{\hat{h_t}}$, to get a stationary i.i.d. distribution, which is suitable for our simulation process,

$$e_t^* = \frac{\hat{\epsilon_t}}{\sqrt{\hat{h_t}}}. \tag{3}$$

The set of standardized residuals, e_t^*, are i.i.d. and therefore suitable for historical simulation if the GARCH model is correctly specified. This is in contrast to empirical returns, which generally do not fulfill the i.i.d. assumption and therefore are not suitable for historical simulation.

Randomly drawn historical standardized residuals need to be scaled with the current volatility. Afterward, they can be used in the conditional mean equation (1) and variance equation (2) to generate pathways for future prices and variances. This random draw is better known as resampling or bootstrapping, which is what filtered historical simulation essentially does. We now randomly draw standardized residual returns from the dataset and use them to generate a single pathway of variances that themselves are used to build our alternative price paths. The randomly drawn standardized residual returns are collected as a vector $\mathbf{e}^*$ of outcomes from the dataset Ψ.

$$\mathbf{e}^* = \{e_1^*, e_2^*, \ldots, e_T^*\}, \qquad \text{where i} = 1, \ldots, T \text{ days}. \tag{4}$$

We use the first drawn standardized residual return from Ψ and scale it using the deterministic volatility forecast for the next day. The deterministic volatility for the next day is constructed as

$$h_{t+1} = \hat{\omega} + \hat{\alpha}(\epsilon_t - \hat{\gamma})^2 + \hat{\beta} h_t. \tag{5}$$

The simulated innovation forecast is created by scaling the randomly drawn standardized residual, e_t^*, with the volatility of period $t+1$, h_{t+1} from Equation (5):

$$z_{t+1}^* = e_t^* \sqrt{h_{t+1}}. \tag{6}$$

This forecast is used to form the one-day-ahead asset price forecast, p_{t+1}^*, using the asset price at time t, p_t:

$$p_{t+1}^* = p_t + p_t(\hat{\mu} r_t + \hat{\theta} z_t^* + z_{t+1}^*). \tag{7}$$

To forecast the volatility for subsequent days ahead we simulate them by recursively substituting the scaled residuals into the variance equation (2). Therefore, our first randomly drawn standardized residual from Equation (3) enters into the one-day-ahead asset price forecast from Equation (7), but it also allows for the simulation of the volatility forecast two days ahead. The two-days-ahead volatility is stochastic as it depends on the simulated return of the first day. To simulate the two-days-ahead asset price we randomly pick another standardized residual and scale it. The volatility three days ahead is generated using the previously drawn second scaled residual and allows the scaling of the third randomly drawn residual and so on up until we reach the number of asset price simulations we want to achieve. The volatility simulation therefore takes the following general form:

$$h_{t+i}^* = \hat{\omega} + \hat{\alpha}(z_{t+i-1}^* - \hat{\gamma})^2 + \hat{\beta} h_{t+i-1}^* \qquad i \geq 2. \tag{8}$$

The process allows the successive scaling of randomly drawn standardized residuals, which allows us to build the asset price pathway. Repeating this process allows us to form various pathways of asset prices. One of the most important aspects when dealing with multiple assets is how to model their correlation. In our scenario building process this is done implicitly by randomly drawing a band of residuals as we use the same standardized residual from the same observation for the price and volatility simulation of each asset. Other approaches that estimate the variance–covariance matrix based on asset returns encounter various problems. Particularly conditional multivariate econometric models, which allow for correlations to change over time, are restricted to a few series at a time. Also, while our approach is able to reduce the dimensions of the problem as the number of parameters increase only linearly with the number of assets that are handled, the dimension of the problem is a quadratic function of the number of assets for models that rely on estimates of the variance–covariance matrix to capture the cross dependencies. For large multi-asset portfolios, the number of pairwise correlations therefore becomes a challenge. Studies, such as Ledoit and Wolf (2003, 2004, 2012, 2017), show that the variance–covariance matrix, correlation coefficients and even their respective signs tend to be unstable. From a statistical perspective, resulting variance–covariance matrices may not be positive definite. When estimating time-varying correlation coefficients independently from each other, there is no guarantee that the resulting matrix satisfies the multivariate properties of the data. To circumvent this problem in our multi-asset framework, we select a random date from the dataset and pick its associated set of residual returns. This set of residual returns is used to model the co-movements between the prices of our multi-asset dataset.

We extend the original methodology for the scenario building process for multiple pathways, doing so in terms of price and volatility path modeling: we adjust the price modeling process such that at day t we use the observed price to model the price and volatility at $t+1$. This improves the quality of our price modeling process significantly. Since the trading strategies tested in this model are implemented using closing prices, there is no risk of look-ahead bias since at the close of day t we know today's price. We use this to model the price and volatility paths for the next t days. In our standard configuration we "reset" the modeling process every 10 days while using a expanding estimation window of 100 days.

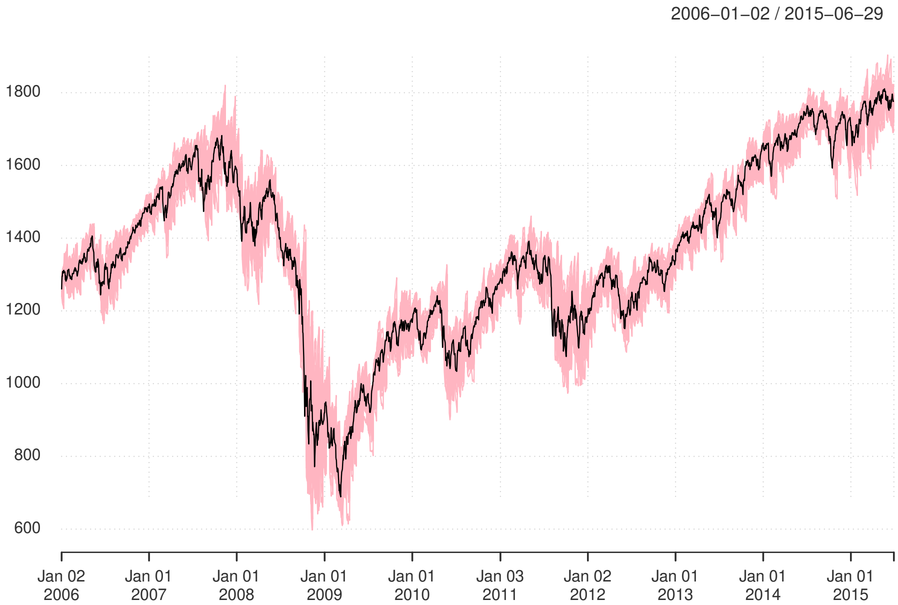
3.1 Parameter Settings

We simulate 200 alternative price paths and reset the simulation process every ten days. We use GARCH(1,1) as our volatility model in the baseline model. We also implement a volatility model detector that automatically detects the best explaining model and applies it. For illustrative purposes and ease of use we provide the results obtained when using the most basic model. Further, Hansen and Lunde (2005) find that of 330 different models none predicts volatility significantly better than GARCH(1,1). Other parameter combinations can be found in the appendix to this paper, where the robustness checks are presented.

3.2 Price Simulations

Before discussing the backtested trading strategies we would like to focus on the scenario building process itself and the resulting simulated prices. We can clearly recognize that overall our simulation results are in line with the development of the observed price series. This follows from the fact that our simulated price paths oscillate around the observed price series, as can be seen in Figure 1, where we plot the observed MSCI World price series in black and the simulated price series in pink. Since we simulate 200 artificial price paths in our baseline model,

Exhibit 1: Observed and Simulated Prices: This figure, based on the MSCI World Index, shows the simulated price paths resulting from our scenario building process in pink, and the observed price series in black.



our simulated prices also show deviations from the observed price. To reduce these deviations we calculate the median of all simulated price paths and compare this price series to the observed price. Again the structure is very similar to the observed price series. For a more detailed examination of this result we provide Figure 2, which plots both series—the observed price in black and the median of our simulated prices in dotted pink. To capture the relationship between either the observed price and the median of our simulated prices or the observed price and all simulated price paths, we report the correlation coefficients. First we calculate the average correlation coefficient between the observed and each simulated price using both the Pearson and the Spearman approach. Both metrics are very high, with a correlation coefficient of 0.985 each. The correlation coefficients between the median of our simulated prices and the observed price are 0.985 using Pearson's and 0.984 using Spearman's approach. We observe stronger deviations from the observed price in times of high volatility, where our simulated prices fluctuate slightly more widely around the observed price series.

Exhibit 2: Observed and Median Simulated Price: In this figure, based on the MSCI World Index, we plot the median simulated price resulting from our scenario building process in dotted pink together with the observed price in black.

4 Trading Strategies

Momentum and trend-following strategies are empirically supported by a variety of academic studies across asset classes, industries, time periods, and specifications (see for example Jegadeesh and Titman (1993), Chan, Jegadeesh, and Lakonishok (1996), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Fama and French (2008), Lee and Swaminathan (2000), and Asness, Moskowitz, and Pedersen (2013)). They are also one of the most widely applied trading strategies in the financial industry (see for example Granger et al. (2014)). One famous trend-following strategy with its roots in technical analysis is the moving average cross. This strategy serves as the benchmark in this paper and we try to outperform it in terms of Sharpe ratio and maximum drawdown.

4.1 Moving Average Cross

As the second word suggests, the moving average cross strategy uses an average of a specific range of data. In our base case we use a moving average of 50 days. This means that we calculate the average price of the last 50 observed closing prices for a specific asset. As the first word implies, this average price moves–in other words, as soon as we have a new observed closing price in our data, we add this to the average calculation and drop the first observation used in the last average calculation. Using again the 50 days moving average, each day the newest closing price is added to the total and the closing price 51 days back is removed. The moving average is therefore a smoothing device to filter noise from the data and has similar properties to many other econometric filters used in economics and finance (see for example Pedersen (2010) or Bruder, Dao, Richard, and Roncalli (2011)). Formally, the moving average can be written as

$$MA_{k_1} = \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1}, \tag{9}$$

where k_1 = moving average period.

Figure 3 plots the price series in black, a 50 days moving average in red, and a 200 days moving average in blue.
The moving average cross system can also be found in the literature under the name double crossover method (see for example Murphy (1999)). This term is used to explain that a buy signal is generated when the faster moving average crosses the slower moving average from below. One of the most famous calibrations is called the Golden/Death Cross (see for example Baba and Nomura

(2005); Fu, Chung, and Chung (2013); Lin, Yang, and Song (2011)). It is a slow trend-following strategy using a 50 days moving average for the fast, and a 200 days moving average for the slow period. Many chart technical applications use this configuration as their default, as it is an event in which short-term momentum overtakes a broader longer-term trend. A buy signal is generated when the 50 days average crosses to above the 200 days average (which is then referred to as a Golden Cross in the financial literature and among traders (see for example Baba, Wang, Kawachi, Xu, and Deng (2003), the *Wall Street Journal*[2], or *Reuters*[3])). This scenario implies an uptrend, whereas a reversed signal (the 50 days moving average crosses the 200 days moving average from above) signals a downtrend and is called a Death Cross. This double crossover strategy lags more than a strategy that is based on the closing price and only one moving average series, but as both series used to generate signals are smoothed the strategy does not get caught if prices whipsaw. As mentioned in Section 2, other studies also support shorter moving average calibrations; however, the best-fitting calibration has to be determined by the trader and depends, among other things, on the desired holding period but also on the transaction costs. Formally, the trading strategy can be stated as follows:[4]

$$Long: \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1} > \sum_{v=-k_2+1}^{0} \frac{P_{t+v}}{k_2}, \tag{10}$$

with moving average periods $0<k_1<k_2$.

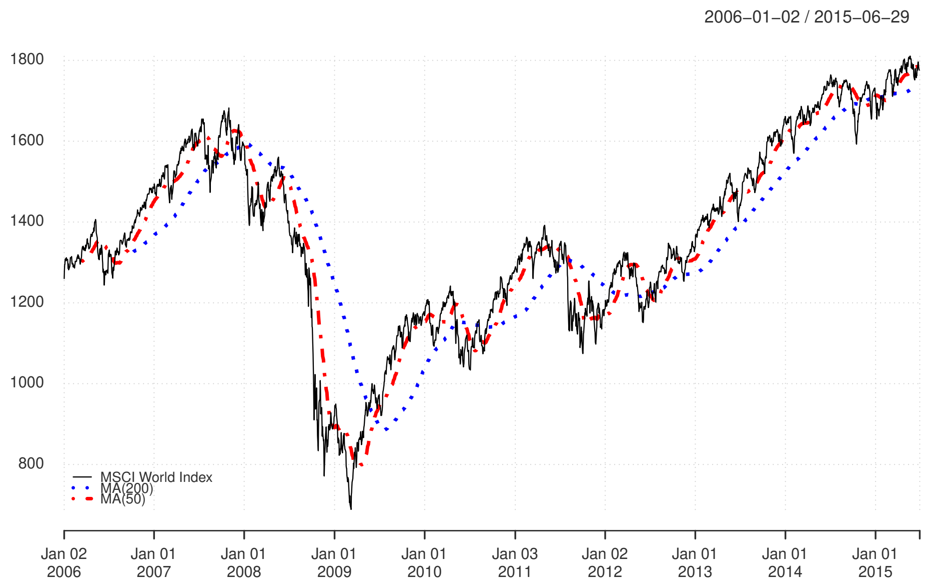
This trading strategy serves as the benchmark strategy for the model tested in this paper.

[2]Wall Street Journal: 'Golden Cross' Boosts Investors' Confidence Entering Earnings Season

[3]Reuters: 'Golden Cross' Adds Shine To Benchmark S&P 500

[4]As our baseline backtests are conducted in a long-only trading environment we only provide the construction methods for long signals. The complete documentation for long–short signals can be found in the online appendix.

Exhibit 3: Moving Average Cross: This chart shows the price series of the MSCI World Index together with two moving averages. The chosen calibration is the same as in our baseline model, with a fast-moving average of 50 days displayed in dash-dotted red and a slow-moving average of 200 days displayed in dotted blue. The strategy is long if the dash-dotted red series is above the dotted blue series. Visually, the strategy seems to be a good indicator for trend detection, with the drawback of being lagging by construction.



4.2 Median Moving Average Cross

We develop a hybrid from the moving average cross strategy that is based on our simulated prices resulting from the scenario generating process. The strategy follows the logic and parametrization used in the moving average cross strategy, but is applied on the median of our simulated prices. The strategy is implemented as follows: We calculate the cross-sectional median of all simulated prices, P^{SBP}. This median simulated price is then smoothed using the fast- and slow-moving averages. In contrast to the benchmark strategy, which looks at today's closing price to determine tomorrow's positioning, the median moving average cross looks at tomorrow's simulated price to generate trading signals for tomorrow. Formally, this can be stated as

$$Long : MA_{k1}\big(\tilde{x}_{0.5}(P^{SBP}_{1,N})\big) > MA_{k2}\big(\tilde{x}_{0.5}(P^{SBP}_{1,N}\big), \tag{11}$$

where $\tilde{x}_{0.5}$ is used as notation for the median, SBP stands for scenario building process, and $P^{SBP}_{1,N}$ indicates the simulated price series starting with the first simulated price path, P^{SBP}_{1}, and ending with the last simulated price path, P^{SBP}_{N}. We use the terms median moving average cross and median simulated price cross interchangeably.

4.3 Probability Strategy

The second strategy we develop based on our simulated prices is the probability strategy. What is important for a trader today is the probability of an asset price rising or falling in the days ahead; in other words, the probability of a positive or negative future return. Our simulated prices can be used to calculate the probability of positive/negative returns based on the empirical distribution of past returns and therefore without the need to specify a theoretical distribution to calculate this probability. We define the probability as

$$\Pr(r_{t+1} > x\%) = \frac{\sum\limits_{n=1}^{N} \left(r^{SBP}_{t+1,n} > x\%\right)}{N}, \tag{12}$$

where N is the number of simulated price paths, $r^{SBP}_{t+1,n}$ is the simulated logarithmic return at time t for the period $t+1$ from simulation run n, and $x\%$ is the chosen return threshold.

In addition to entering a trade, the trader can also determine the probability threshold—that is to say, a long position is opened if the probability of a return larger than $x\%$ over the next n days is larger than (or equal to) $y\%$; therefore,

$$Long : \Pr(r_{t+1} > x\%) \geq y\%, \tag{13}$$

where, as described above, $x\%$ is the return threshold and $y\%$ represents the specified probability threshold. In our baseline configuration we set the probability target, $y\%$, equal to 50 percent, but impose a greater-than restriction instead of a greater-than-or-equal-to restriction.

5 Data & Empirical Results

The price data we use in this paper was collected from the Bloomberg Terminal with daily frequency over a time period from December 2004 until June 2015. As some data points of this initial data sample are used in our scenario building process to generate artificial price series, the testable data sample is from January 2006 until June 2015, as reported in Figures 1, and 2. This period is—again—shortened due to the data needed for calibrating the trading strategies. This time, the amount of data needed for calibrating the trading strategies equals the slow-moving average, which is 200 days in our base case. Therefore, the tested trading period is from July 2006 until June 2015. In Table 1 we report the correlations between all tested assets, including those used as robustness checks in the online appendix. While the correlation analysis documents a strong co-movement between the tested time series with correlations of between 0.60 and 0.97, Figure 4 plots how the assets developed over time and—thereby—shows significant differences in certain periods. Remarkably low correlation figures are reported for the Emerging Markets Index, which only appears to be highly correlated to the Pacific market. We document a high correlation coefficient for the major developed markets—the USA, represented by the S&P 500, and Europe—as well as for Germany's DAX Index. As the biggest part of the underlying securities in the investment universe of the MSCI World is from developed markets, the high correlation of these indices is expected. Table 2 reports the descriptive statistics based on the return series of every tested asset. Over the entire testing period, the smallest daily return of the MSCI World is -7.3%, which is slightly higher than the minimum respective returns of Europe and the DAX. For the S&P 500 we report a lower minimum return of -9.46%, but find even greater daily maximum negative returns for emerging markets and the Pacific area, with -9.96% and -13.16%, respectively. In terms of maximum daily return figures, the data sample is more evenly distributed around 10%, with Pacific being the only outlier with a lower maximum return, of 8.32%. We report negative skewness for all assets apart from

the DAX, which has a small, but positive skewness. The DAX is also the index with the lowest kurtosis across all tested assets, followed by Europe, Emerging Markets, and Pacific. The US market experiences the highest kurtosis during our observation period. In terms of volatility, emerging markets and Pacific equities together with the DAX fluctuate the most. We decide to use these regional and country-specific equity indices in our empirical analysis to cover the largest part of the global, liquid equity universe.
In this section we discuss the empirical results for two assets: the MSCI World Index and Standard & Poor's 500 Index. The empirical results for other assets and a variety of robustness checks will be provided upon request and will be collected and documented in our online appendix.

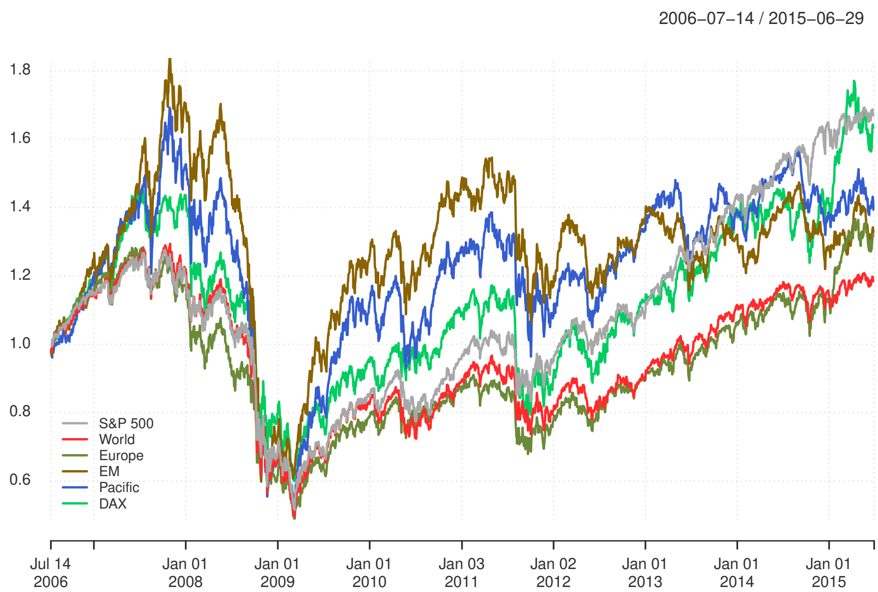
	S&P 500	World	Europe	EM	Pacific	DAX
S&P 500	1	0.8756	0.9018	0.6415	0.8508	0.9544
World	0.8756	1	0.9689	0.6301	0.7592	0.8890
Europe	0.9018	0.9689	1	0.6034	0.7499	0.9306
EM	0.6415	0.6301	0.6034	1	0.9299	0.7521
Pacific	0.8508	0.7592	0.7499	0.9299	1	0.8895
DAX	0.9544	0.8890	0.9306	0.7521	0.8895	1

Exhibit 1: This table reports the Spearman correlation between the tested assets. The time period used is from 2006-07-14 to 2015-06-29. The indices World, Europe, Emerging Markets (EM), and Pacific are all based on MSCI data.

	S&P 500	World	Europe	EM	Pacific	DAX
Observations	2737	2737	2737	2737	2737	2737
Minimum	-0.0946	-0.0733	-0.0792	-0.0996	-0.1316	-0.0743
Quartile 1	-0.0041	-0.0042	-0.0049	-0.0055	-0.0057	-0.0057
Median	0.0005	0.0007	0.0007	0.0010	0.0008	0.0007
Mean	0.0003	0.0002	0.0003	0.0003	0.0003	0.0004
Quartile 3	0.0055	0.0051	0.0059	0.0070	0.0071	0.0068
Maximum	0.1096	0.0910	0.0957	0.1007	0.0832	0.1080
Skewness	-0.3323	-0.4641	-0.1304	-0.5013	-0.7807	0.0319
Kurtosis	11.7446	9.6063	7.7957	8.7521	8.7664	6.9439
Std Dev	0.0125	0.0107	0.0120	0.0131	0.0143	0.0137

Exhibit 2: This table shows the descriptive statistics. The time period used is from 2006-07-14 to 2015-06-29. The indices World, Europe, Emerging Markets (EM), and Pacific are all based on MSCI data.

Exhibit 4: Tested Price Series: This chart shows the price development of our tested price series over the time period used in our main analysis, from 2006-07-14 to 2015-06-29.



5.1 MSCI World

The MSCI World Index captures large- and mid-cap companies across 23 developed-markets countries. With more than 1,500 constituents, the MSCI World Index covers approximately 85 percent of the free-float-adjusted market capitalization in each country. To visualize our empirical findings, we provide Figures 5 and 6; the first shows the cumulative return generated by the respective trading strategy. In each of these figures we plot four data series: the black series is the buy-and-hold strategy, which buys the asset at $t = 0$ and holds it until $t = T$. This is plotted for illustration purposes only, as we do not try to outperform the buy-and-hold strategy. We will nonetheless refer to the buy-and-hold strategy if such reference is beneficial. The red series is the moving average cross strategy, the blue line represents the median simulated price strategy, and the green line represents the probability strategy.

As can be seen in Figure 5, the probability-based strategy achieves the highest cumulative return. The strategy benefits significantly from its ability to correctly predict the market stress generated during the financial crisis. In contrast to the buy-and-hold strategy, the probability strategy is able to circumvent the large drawdowns of 40–60 percent as can be seen in Figure 6. The probability strategy does not capture the recovery of asset prices to the same extent as does the buy-and-hold strategy. The probability strategy continues to outperform the buy-and-hold and the benchmark strategies until the end of the data sample, mainly—as in the example explained above—due to its ability to predict coming market stress. The probability strategy is, by its nature, a defensive strategy, with the primary goal of avoiding drawdowns. Therefore, it does not react as strongly to market recoveries as the underlying asset itself, but in terms of its Sharpe ratio strongly outperforms the buy-and-hold as well as the benchmark strategy, the moving average cross. All this results in a Sharpe ratio for the probability strategy that is almost 35 percent larger relative to our benchmark strategy. The behavior of the median moving average cross is very similar to that of the probability strategy over the entire testing period. They were able to avoid the huge drop in the price level caused by the financial crisis but not as well as was the benchmark strategy. The strategies based on simulated prices are, however, able to better catch the market recovery than is the benchmark strategy. In contrast to during the financial crisis, both simulation-based strategies perform better than the benchmark strategy in the mid-2011 market correction. This outperformance is the fundament for the better risk-return properties of our simulation-based strategies. In addition, both strategies perform better from the end of 2014 until the end of our data sample, which leads to even stronger backtesting results in favor of the median moving average cross and the probability strategies. Table 3 contains the risk-adjusted performance metrics for all tested strategies. The median moving average cross generates an outperformance of 31 percent in terms of its Sharpe ratio relative to our benchmark. The maximum drawdown of both the probability and the median simulated price strategies is 25%. This is a reduction of 5% or almost 14% relative to the benchmark strategy. Also, both simulation-based strategies generate a higher return than the benchmark. This fact is mirrored in the tracking error and information ratio, which are 0.35 and 0.32, respectively. The Bernardo and Ledoit ratio, which relates the positive to the negative returns, also shows a better performance relative to the benchmark strategy. As the return generated by the simulation-based strategies is higher than the return achieved by the moving average cross strategy and the drawdowns are reduced, the Burke and Calmar ratios, which relate the aforementioned metrics to one another, cast our simulation-based strategies in a favorable light. Omega with a threshold of zero is calculated at 1.0982 and 1.0959, respectively for the probability and median simulated price strategy and is therefore significantly larger than the 1.0743 of the benchmark strategy. Table 4 shows that our active trading strategies are able to reduce the percentage of losing trades, while also reducing the percentage of winning trades. This is also reflected in the down percent metric, which reports the outperformance of our simulation-based strategies versus the benchmark. Therefore, the simulation-based strategies capitalize particularly when markets dip. This is also mirrored in the statistical moments of the simulation-based strategies, which experience a skewness of -0.5361 for the probability strategy and -0.5348 for the median moving average cross strategy. In comparison, we report skewness for the benchmark strategy of -0.6283. This is in line with the risk-adjusted metrics discussed above, such as the ratios of Bernardo and Ledoit, Burke, and Calmar. While the kurtosis for the simulation-based strategies slightly increases relative to the benchmark strategy, overall—and also mirrored in the Omega ratio of Table 3—they have more desirable statistical moments than the benchmark strategy.

Exhibit 5: Cumulative Return: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

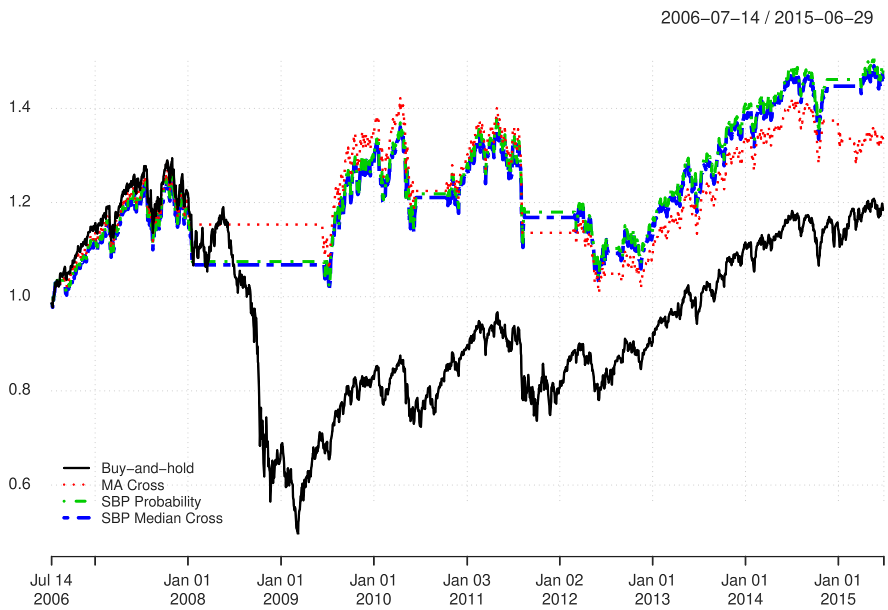


Exhibit 6: Drawdown: This chart shows the maximum drawdowns of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Return	0.0184	0.0315	0.0428	0.0417
Std Dev	0.1799	0.1057	0.1069	0.1069
Worst Drawdown	0.6173	0.2917	0.2487	0.2454
Sharpe R. (Rf = 0%)	0.1024	0.2979	0.4006***	0.3905***
Tracking Error			0.0326	0.0325
Information R.			0.3485	0.3157
Bernardo & Ledoit R.	1.0375	1.0743	1.0982	1.0959
Burke R. (Rf = 0%)	0.0282	0.0812	0.1104	0.1075
Calmar R.	0.0298	0.1079	0.1722	0.1702
Omega (L = 0%)	1.0375	1.0743	1.0982	1.0959

Exhibit 3: This table shows the annualized Sharpe ratio, return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index. Additional performance metrics, such as the information, Bernardo and Ledoit, Burke, and Calmar ratios and the Omega, are provided. The corresponding significance signs are (applying the approach presented in Ledoit and Wolf (2008)) . significant at $p < 0.1$, * significant at $p < 0.05$, ** significant at $p < 0.005$, *** significant at $p < 0.001$. The moving averages are specified as follows: the slow-moving average is equal to 200 and the fast-moving average is equal to 50. The time period tested is from 2006-07-14 to 2015-06-29. Number of simulations is equal to 200, with number of steps equal to 10. The backtests are conducted in a long-only trading environment.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
% Winners	0.5413	0.3787	0.3748	0.3744
% Losers	0.4557	0.3128	0.3055	0.3059
Up Capture			0.9681	0.9683
Down Capture			0.9432	0.9456
Up Number			0.9672	0.9672
Down Number			0.9562	0.9562
Up Percent			0.0000	0.0000
Down Percent			0.0438	0.0438
Skewness	-0.4531	-0.6283	-0.5361	-0.5348
Kurtosis	8.6963	6.2398	6.4192	6.4195

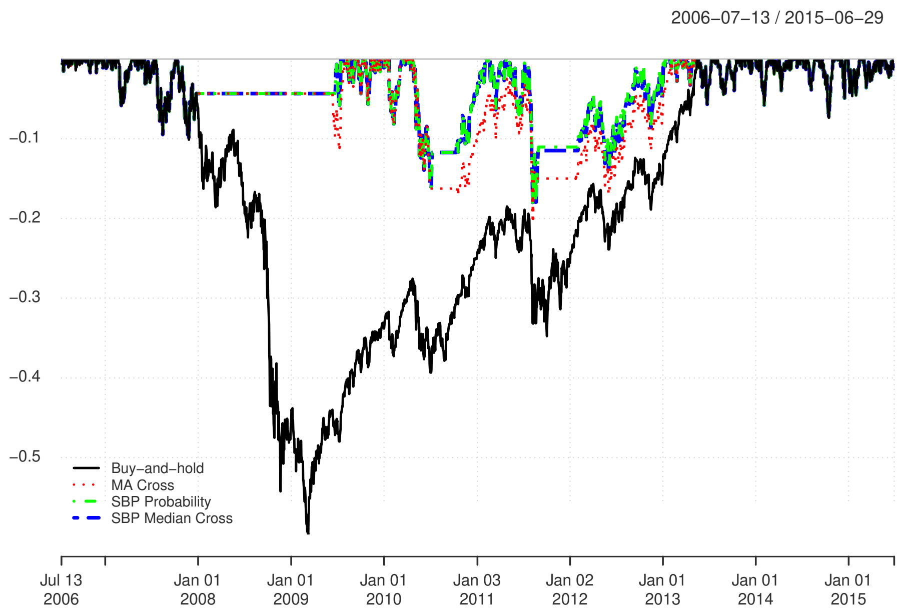
Exhibit 4: This table shows the percentage of winning/losing trades, information on up- and down-market performance, and the statistical moments for the asset class equity and the asset MSCI World Index. The moving averages are specified as follows: the slow-moving average is equal to 200 and the fast-moving average is equal to 50. The time period tested is from 2006-07-14 to 2015-06-29. Number of simulations is equal to 200, with number of steps equal to 10. The backtests are conducted in a long-only trading environment.

5.2 Standard & Poor's 500

The S&P 500 includes 500 leading large-cap US companies and captures approximately 80 percent of the available market capitalization. To visualize our empirical findings, we provide Figures 7 and 8. The first shows the cumulative return generated by the respective trading strategy; the second plots and compares the drawdowns each strategy experiences. Clearly, the trading strategies based on our simulated prices outperform the benchmark strategy in terms of cumulative return. The behavior of all tested trend-following strategies is very similar in terms of cumulative return as well as in terms of drawdowns. However, in spring 2010 the simulation-based strategies are able to close their positions at a better time than the benchmark strategy does, and the benchmark strategy loses significantly more, as can be seen in Figure 8. Afterward, the signals created by the three trading strategies are approximately identical until mid-2011, when the benchmark strategy leaves its long position open for too long. In contrast, both simulation-based strategies close out their long positions earlier resulting in a lower drawdown in this period. This again results in amplified outperformance relative to the benchmark strategy. These findings, translated into numbers, are presented in Table 5. The median moving average cross strategy achieves the highest Sharpe ratio with 0.8022, or, 14 percent higher than the benchmark's Sharpe ratio. The probability strategy has a Sharpe ratio of 0.7997, which is almost as high as that of the median moving average cross strategy. As can be seen in Table 5, the outperformance is due to the higher annualized return, whereas the volatility of both simulation-based strategies is slightly higher than that of the benchmark strategy. It is important to note that the benchmark strategy reduces the maximum drawdown by approximately 65 percent relative to the buy-and-hold strategy even though its main disadvantage is its lagging behavior in terms of trading signal generation. The simulation-based strategies both experience a maximum drawdown of 18 percent, which is a 10 percent reduction relative to the benchmark strategy. With 0.4413 and 0.4313, the information ratio for the S&P 500 backtests are even higher than the previously reported results for the MSCI World Index. With the sum of positive returns being larger than the negative counterpart, the Bernardo and Ledoit ratio demonstrate the superior performance of the simulation-based strategies. The Burke and Calmar ratios, both relating the generated return to the drawdowns experienced by a strategy, reflect the outperformance achieved by our simulation-based strategies. Omega with a threshold of zero is calculated at 1.1918 and 1.1924 for the probability and median simulated price strategies and is therefore significantly larger than the 1.1674 of the benchmark strategy. In Table 6 we document that both the percentages of winning and losing trades are lower for the simulation-based strategies relative to the benchmark. The performance metrics down capture and down percent, however, show, that the simulation-based strategies outperform the benchmark strategy in down markets. This feature was also observed in the backtests of the MSCI World data and is therefore robust. In terms of statistical moments, the median moving average cross strategy and the probability strategy experience a skewness of -0.6015 and -0.6017, respectively—this is lower than the reported skewness for the benchmark strategy, of -0.6425, and in line with the results of down capture measures, as well as risk-adjusted measures such as the ratios of Bernardo and Ledoit, Burke, and Calmar. While the kurtosis is slightly higher for the simulation-based strategies with 7.7814 and 7.7799 versus the benchmark strategy with 7.6557, this, in combination with the reduced skewness, is a very attractive property for the trading strategies—again, this is in line with the results reported for Omega in Table 5.

Exhibit 7: Cumulative Return: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the S&P 500 Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

Exhibit 8: Drawdown: This chart shows the maximum drawdowns of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the S&P 500 Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.



	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Return	0.0568	0.0862	0.0999	0.1002
Std Dev	0.2096	0.1232	0.1249	0.1249
Worst Drawdown	0.5962	0.2007	0.1803	0.1803
Sharpe R. (Rf = 0%)	0.2710	0.6996	0.7997***	0.8022***
Tracking Error			0.0317	0.0318
Information R.			0.4313	0.4413
Bernardo & Ledoit R.	1.0770	1.1674	1.1918	1.1924
Burke R. (Rf = 0%)	0.0894	0.2384	0.2749	0.2758
Calmar R.	0.0953	0.4297	0.5540	0.5558
Omega (L = 0%)	1.0770	1.1674	1.1918	1.1924

Exhibit 5: This table shows the Sharpe ratio, return, standard deviation, and maximum drawdown for the asset class equity and the asset S&P 500 Index. Additional performance metrics, such as the information, Bernardo and Ledoit, Burke, and Calmar ratios and the Omega, are provided. The corresponding significance signs are (applying the approach presented in Ledoit and Wolf (2008)) . significant at $p < 0.1$, * significant at $p < 0.05$, ** significant at $p < 0.005$, *** significant at $p < 0.001$. The moving averages are specified as follows: the slow-moving average is equal to 200 and the fast-moving average is equal to 50. The time period tested is from 2006-07-14 to 2015-06-29. Number of simulations is equal to 200, with number of steps equal to 10. The backtests are conducted in a long-only trading environment.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
% Winners	0.5362	0.4039	0.4018	0.4022
% Losers	0.4292	0.3145	0.3098	0.3098
Up Capture			0.9826	0.9826
Down Capture			0.9561	0.9556
Up Number			0.9767	0.9767
Down Number			0.9741	0.9741
Up Percent			0.0000	0.0000
Down Percent			0.0259	0.0259
Skewness	-0.3317	-0.6425	-0.6015	-0.6017
Kurtosis	10.6462	7.6557	7.7814	7.7799

Exhibit 6: This table shows the percentage of winning/losing trades, information on up- and down-market performance, and the statistical moments for the asset class equity and the asset S&P 500 Index. The moving averages are specified as follows: the slow-moving average is equal to 200 and the fast-moving average is equal to 50. The time period tested is from 2006-07-14 to 2015-06-29. Number of simulations is equal to 200, with number of steps equal to 10. The backtests are conducted in a long-only trading environment.

5.3 Other Equity Indices

In this subsection, we present a qualitative summary of our backtesting results based on other underlying assets—namely, the MSCI indices on Europe, Emerging Markets, and Pacific and the country index on the DAX. For these assets we document significant outperformance in all risk-adjusted performance metrics. For the European, Pacific, and DAX indices, the skewness of the simulation-based trading strategies is less negative than that of the benchmark strategy, thus reducing the large negative returns. While the skewness is more negative for the simulation-based trading strategies when applied to the data of emerging markets, the Omegas of 1.0857 for the probability and 1.0818 for the median moving average cross strategies compared to that of the benchmark strategy, 1.0443, provides evidence of desirable statistical properties. Overall, the empirical evidence based on other assets supports the findings of the two main study results based on the MSCI World and S&P 500.

6 Conclusion

In this paper we simulate alternative price paths based on the observed, empirical distribution of past returns. This allows us to circumvent the problem of pre-specifying a distribution function that our simulated returns have to follow. Our empirical results suggest that using a simulation process that is able to capture the characteristics of a price and volatility series it is possible to improve trend-following trading strategies. Based on our simulated prices we develop two trading strategies: the probability strategy looks at the probability of tomorrow's return being larger than a specified threshold, whereas the median simulated price strategy uses the median of all simulated prices and generates trading signals with the same logic as does the benchmark strategy, the moving average cross system. However, the probability and the median simulated price strategy use tomorrow's simulated price data to create tomorrow's trading signal, which is then traded on the underlying asset. We test our trading strategies against the moving average cross system, which is widely applied in the financial industry (see for example Granger et al. (2014) or Hurst et al. (2017)). Our results are stable across a variety of chosen parametrizations and, more importantly, across several assets. The methodology presented in this paper is able to improve the existing trend-following strategy, the moving average cross, in terms of a large range of financial performance metrics, including the ratios of Sharpe, Bernardo and Ledoit, and Burke, to name but a few. Both trading strategies, the probability and the median simulated price strategy, are able to detect increased market stress and therefore outperform the benchmark strategy. Especially either in times of high volatility or when, by its nature, an asset exhibits high volatility, the probability and the median simulated price strategies are able to reduce drawdowns. This leads to their significant outperformance relative to the benchmark strategy. Evidence suggests that particularly in down markets the simulation-based strategies have a significant edge over the plain-vanilla trend-following strategies. We test our methodology on various assets and report the empirical findings for the indices MSCI World and Standard & Poor's 500 in this paper. Additionally, we conduct several robustness checks in order to challenge the main findings of our baseline results. To do so, we test additional assets—namely, the MSCI indices for Europe, Emerging Markets, and Pacific and the DAX Index. While each of these underlying assets performs differently over the observation period, our simulation-based trading systems outperform the benchmark strategy in every tested environment in every reported performance metric. Additionally, we alter the calibration of the moving average cross system itself—that is, we change the parametrization of the fast- and slow-moving averages. We do this not only to test our main results on robustness but also because different studies report different moving average calibrations to perform best. We therefore want to show that our approach of combining the scenario building process with the trend-following strategy improves the generated trading signals irrespective of the calibration itself. Therefore, the empirical results of our robustness checks support our main findings. While the results presented in this paper come from a long-only trading environment, we conduct the same empirical study in a long–short and a short-only environment. We also analyze the impact of the simulation horizon on the Sharpe ratio achieved by the respective trading strategy and find that shorter simulation horizons perform best. Even though our strategies outperform the buy-and-hold strategy most of the time, it is important to recall that this is not the goal of this paper. Our strategies have to outperform the moving average cross system using the same specification as the benchmark strategy. We therefore do not adjust the moving average cross parametrization to better fit a specific asset. Our only goal is to improve the trend-following strategy. Fitting the strategy calibration to the price series to improve the performance and exposing our results to possible curve fitting is not our intention and is left to the trader if desired. We provide a methodology that can be widely applied to improve strategies and make them more robust for a large universe of assets.

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